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Human Capital and Earnings Inequality in Brazil, 1988–1998: Quintile Regression Evidence

G. Reza Arabsheibani,[†] Francisco Galrão Carneiro,[*] and Andrew Henley[†]

Abstract

This paper undertakes an empirical examination of rates of return to human capital for men in Brazil through the period of macroeconomic stabilization and trade liberalization, using data from the PNAD household surveys. Simultaneous quintile equations are estimated to gain a picture of the impact of human capital on earnings across the hourly earnings distribution. We conclude that there is evidence for growing inequality in rates of return to education in Brazil. However we find evidence that education is no longer used as a screening device in the labor market, but rather rewarded for its innate association with higher productivity. Although increases in rates of return to education have been more pronounced at the top of the earnings distribution, this has not led to increased inequality. This is because levels of education and other labor market-rewarded endowments have increased and offset the rate of return effect.

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[†] School of Management and Business, University of Wales Aberystwyth, UK.
[*] The World Bank – Poverty Reduction and Economic Management (PREM).

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1. Introduction

A far-reaching program of macroeconomic stabilization and rapid liberalization of trade in a developing economy are likely to have important and widespread consequences for the labor market. However there appears to be little evidence from a number of recent examples for the Stolpher-Samuelson theorem that trade liberalization in a developing economy will increase the relative demand for relatively abundant low-skilled labor, and so reduce income inequality.[1] The Brazilian case has been particularly well-researched and there is an emerging conventional wisdom that, despite the upheavals of price and exchange rate stabilization and tariff reduction, earnings inequality in Brazil has remained stubbornly high between 1980 and the present (Dickerson et al., 2001; Green et al., 2001). One explanation for this is that steadily rising average levels of schooling have offset increased demand for skilled labor. At first glance this is a persuasive suggestion. In the sample of Brazilian male workers used in the present paper, average years of education for men have risen by almost one year between 1988 and 1998, and the rate of illiteracy has fallen from 16.6 to 11.6 per cent. Research has also established that rates of return to education in Brazil are low for primary schooling but very much higher for advanced levels of education. This may contribute significantly to Brazil's highly unequal distribution of earnings (Lam and Levinson, 1992). However while this may be true at the mean of the earnings distribution, little is known about rates of return across the range of this wide distribution. Furthermore, there is evidence that inequality peaked in the late 1980s and has been falling since, in contrast to what has happened elsewhere in the developing world and in particular in Latin America. If so this points to the possibility that important changes in the levels of and rates of return to education have taken place since the late 1980s. Consequently the reform experience may have been a very different one for workers in different positions in the income distribution.

Protected product markets in the developing world prior to the early 1990s appear to have been associated with protected labor markets in Brazil in particular (Carneiro and Henley, 1998; Carneiro, 1998). Liberalization of the economy to overseas trade exposes domestic producers significantly to greater product market competition and this in turn serves to introduce much stronger forces of competition to the labor market. An important consequence of this process is that education ceases to serve as a device for rationing (screening) workers' access to economic rents. Rather education, if it reflects the acquisition of internationally marketable skills, begins to be associated with inherent productive potential. Whether the benefits of this process accrue more to those with lower or higher levels of education is a matter for empirical investigation. In common with other Latin American cases, such as Mexico, there is evidence that tariff protection was highest in sectors where employment of the least skilled was dominant (Mollick, 2002; Arbache and Corseuil, 2001). Overall there appears to have been little or no assessment of whether apparently high rates of return to formal education represent a genuine return to valuable skills acquired at school, or simply reflect the ability of the more educated to signal innately higher productivity to the labor market.

This paper undertakes an empirical examination of these questions through the estimation of simultaneous quintile human capital equations. This is in order to gain a picture of the impact of human capital on earnings across different point of the distribution of earnings in Brazil. This exercise is performed a sample of male workers drawn from

[1] See discussion and further references in Green et al., 2001.

household survey data from before, during and after the stabilization and liberalization program of the early 1990s. We conclude that there is evidence for growing inequality in rates of return to education in Brazil, but evidence that education is no longer used as a screening device in the labor market, but rather rewarded for its innate association with higher productivity. Although increases in rates of return to education have been more pronounced at the top of the earnings distribution, this has not led to increased inequality. This is because levels of education and other labor market-rewarded endowments have increased and offset the rate of return effect.

The remainder of the paper is structured as follows. Section 2 discusses the empirical method used. Section 3 describes the data source used. Section 4 presents results and section 5 concludes.

2. Empirical Approach

An important issue on the productivity of education concerns whether formal education acts as a screen, separating more able (and educated) individuals from the less able (and educated). The screening hypothesis (Arrow, 1973) observes that at the point of hiring workers' productivity is unknown to employers and argues therefore that employers use education as a proxy for latent productivity. In competitive sectors of the labor market productivity will matter and so returns to education will be higher. In non-competitive sectors of the labor market returns to subsequent education after hiring will be lower. It is therefore possible that the value of education as a screen may vary across the earnings distribution because of differing degrees of competition. In particular screening may be more important in the top of the distribution, where insider power may be more important.

The empirical literature on screening distinguishes between the weak form and strong form of the hypothesis (Psacharopoulos, 1979; Arabsheibani and Rees, 1998). The weak form states that employers will pay a higher initial salary to recruits with higher levels of education, but is agnostic about the shape of the subsequent experience-earnings profile. The strong form states that employers will continue to pay high salaries even after observing working on the job, because education continues to enhance productivity as experience on the job rises. However the experience-earnings profiles of an educated worker will converge over time with that of a non-educated worker, as the original hiring "mistake" is gradually corrected. Psacharopoulos (1979) proposes what has become known as the P(sacharopoulos) test as a method of empirical investigation.

Assume that log hourly earnings for individual i, y_i , are determined according a Mincerian earnings function of the following form:

$$y_i = a_0 + a_1 S_i + a_2 S_i^2 + a_3 E_i + a_4 E_i^2 + a_5 S_i E_i + b' Z_i + u_i \tag{1}$$

where S is years of education, E is years of experience, Z are other socio-economic variables affecting earnings, a_j and b are coefficients and u is a disturbance term. The inclusion of the interaction term between years of education and years of experience provides a straightforward test of convergent experience-earnings profiles under the strong screening hypothesis (Lee, 1980). If the hypothesis holds then $a_5 < 0$, otherwise $a_5 \geq 0$.

Previous research has shown that modeling average earnings (i.e. OLS) fails to reveal that the effect of education on earnings is non-constant across the conditional wage distribution (Buchinsky, 1994, 1998; Machado and Mata, 2001; Bauer and Haisken-DeNew, 2001; Hartog, Pereira and Vieira, 2001). This reinforces the need to investigate the screening hypothesis across the earnings distribution. An appropriate empirical strategy is to fit the earnings model across different points in the conditional sample distribution, using the quintile regression method. This was first introduced by Koenker and Bassett (1978). Assume y_i , $i = 1,\ldots,n$, is a sample of observations on log earnings, and that X_i is a K x 1 vector comprising the education, experience and other control characteristics contained on the right-hand side of equation (1). The quintile regression model can be expressed as:

$$y_i = X_i'\beta_\theta + u_{\theta i},\ \ \mathrm{Quant}_\theta(y_i \mid X_i) = X_i'\beta_\theta,\ \ \theta \in (0,1) \tag{2}$$

where Quint$_\theta(y_i \mid X_i)$ denotes the quintile θ of log earnings conditional on the regressor vector. Following Koenker and Bassett (1978), the regression quintile θ can be defined as the solution to the problem:

$$\min_\beta \frac{1}{n}\left[\sum_{i:y_i \geq x_i'\beta} \theta\left|y_i - x_i'\beta_\theta\right| + \sum_{i:y_i < x_i'\beta}(1-\theta)\left|y_i - x_i'\beta_\theta\right|\right] = \min_\beta \frac{1}{n}\sum_{i=1}^{n}\rho_\theta(u_{\theta i}) \tag{3}$$

where $\rho_\theta(.)$ is known as the "check function" and is defined as:

$$\rho_\theta(u_{\theta i}) = \begin{cases} \theta u_{\theta i} & \text{if } u_{\theta i} \geq 0 \\ (\theta - 1)u_{\theta i} & \text{if } u_{\theta i} < 0 \end{cases}$$

Estimation is by minimizing the sum of weighted absolute deviations and can be performed using linear programming methods (Buchinsky 1998). An estimated variance-covariance matrix for the chosen system of quintile regressions is obtained using a bootstrap re-sampling method using Stata Release 7 (StataCorp 2001). Quintile regression coefficients can be interpreted by considering the partial derivative of the conditional quintile with respect to a particular regressor. This equates to the marginal change in the θth conditional quintile due to a marginal change in the regressor. It is however important to note that a sample individual who is in the θth conditional quintile may no longer remain in that quintile if his or her characteristic measured by the particular regressor changes. So, for example, rates of return to additional years of schooling or experience as captured by the estimated coefficients apply to an individual remaining in a particular conditional quintile.

3. Data Source and Description

The present paper uses data drawn from the 1988, 1992 and 1998 Brazilian household surveys (Pesquisa Nacional por Amostra de Domicílios, PNAD). The PNADs are a series of nationally representative household surveys conducted more or less annually since 1976, using a consistent methodology by the Instituto Brasileiro de Geografia e Estastistica (IBGE). All members of each household over ten years in age are asked detailed questions concerning their labor market activity during one week in September. Each survey covers a nationally representative sample of households. The sample size has risen progressively from 69,066 households in 1988, to 94,171 in 1992 and 112,434 in 1998. The present paper draws from these households the sample of employed men between the ages of 18 and 65, who report earnings and hours of work data and information on human capital and the other controls used for estimation purposes. This results in a sample of 65,002 in 1988, 67,880 in 1992 and 74,003 in 1998. The 63% increase in the number of households sampled over the decade appears, therefore, to have resulted in better coverage of households with fewer or no employed males.

Hourly earnings are defined as reported monthly earnings divided by 4.33 and then divided by reported weekly hours of work. Table 1 reports summary descriptive information for each year on log (hourly earnings), along with descriptive statistics on years of education, years of experience[2] (defined as age - (6 + years of schooling)) and the regional, metropolitan, urban and racial composition of the samples. Real hourly earnings fall between 1988 and 1992 but rise thereafter. The standard deviation in hourly earnings drops somewhat over the period, particularly between 1988 and 1992. This narrowing in the male earnings distribution is further apparent in the movement in the gap between the 75th and 25th percentiles, and in particular in the narrowing in the gap between the 90th and 10th percentiles, shown at the bottom of the Table.

Sample average years of schooling increase by 0.9 years between 1988 and 1998. Undoubtedly this is the result of younger more educated male cohorts entering the labor force. There is also a reduction in average experience of just over 1 year between 1988 and 1998. In part this is consistent with the increase of the average length of time spent in education. However the mean and median product of education and experience both show a marked increase.

Figures 1 to 3 describe the log hourly earnings distribution in each year through the estimation of univariate Kernel density functions.[3] Vertical lines of each figure identify the position of the 10th, 25th, 50th, 75th and 90th percentiles of the distribution in each case. Visual inspection reveals that the dispersion of these percentile points narrows over time. A further feature of note is that in 1988 and in 1992 in particular the shape of the distribution reveals a mode at almost exactly the 25th percentile. However by 1998 the shape of the distribution changes considerably, with the mode moving much closer to the median.

4. Empirical Results

Key results (coefficients a_1 to a_5) for earnings function estimates for 1988, 1992 and 1998 are presented in Table 2. For each year the table firstly shows OLS estimates and then simultaneous quintile regression estimates for the 10th, 25th, 50th, 75th and 90th quintiles. For each year a Wald test for the null hypothesis of equality of the coefficients across the quintiles is decisively rejected. The reported coefficients suggest considerable variation in the education-earnings and experience-earnings profiles at the different points in the earnings distribution. We shall discuss rates of return to education and experience shortly.

The education-experience interaction coefficient is negatively signed and statistically significant at the sample mean (OLS) and for the 10th, 75th and 90th conditional quintiles for 1988 and 1992. However at the sample mean (OLS) and for every quintile below the 90th the coefficient is positively signed and statistically significant. This suggests that prior to the mid 1990s for those at the very bottom and those in the higher part of the earnings distribution

[2] The 1992 and 1998 surveys provide information on experience with the current employer. However the explanatory power of the earnings equations are substantially lower using this definition.

[3] Estimated using the Epanechnikov kernel estimator with 200 evaluation points over range of the distribution.

formal education appears to have acted as a signal for innate ability rather than provided human capital. Experience-earnings profiles appear to converge, albeit slowly, after initial hiring. However by 1998 there appears to have been a shift in the way the labor market functions, with education having more inherent productivity-enhancing value.[4]

Tables 3 and 4 report rates of return to additional years of education and experience respectively, for each year at the mean (OLS) and for each conditional quintile. Marginal rates of return are calculated for levels of education and experience spread across the sample range. The estimates reveal that rates of return to additional years of education are much higher at already high levels of education. So for example an additional year of education for someone with only 2 years of formal education will yield a 12 to 13 percent increase in earnings at the mean in 1988, a 10 to 11 percent increase in 1992 and only a 7 to 8 percent increase in 1998. By contrast at the higher levels of initial education the rates of return to additional education are much higher: 23 to 24 percent at the mean in 1988, 20 to 22 percent in 1992 and rising to 26 percent in 1998. Clearly education to college level has become significantly more valuable in the labor market by the late 1990s. The "stretching out" of returns at the top end of the distribution, and at the top of the range of education and experience arises because of the change in the sign of the interaction effect between the two, indicative of a move from non-competitive screening behavior for more highly paid jobs, to a genuinely competitive labor market in which education is rewarded because of its association with productivity.

Table 3 also reveals that rates of return to an additional year of education are between 4 and 7 percentage points higher at the 90th quintile compared to the 10th. If this fact is combined with the change over time in the marginal rate of return to education, it makes for growing inequality in the returns to education and points to a very important force for greater earnings inequality. However set against this we must also note, from Table 1, that average levels of education in the male population have been rising over the period in question. An increased supply of educated workers does not appear to have compressed earnings. Rather the increase in demand for skills appears to have outstripped the increase in supply, with the effect that the price has risen. The Brazilian economy appears, in the mid 1990s, to have moved from one in which at the top of the earnings distribution, education is used to signal inherent ability to one where education has become genuinely productive.

Table 4 shows how marginal rates of return to experience change over the sample range. There are three features to the Table. Firstly rates of return fall sharply as experience increases – an indication of the quantitative importance of the statistically significant squared term in experience in all the reported regressions. Between 30 and 40 years of accumulated experience additional experience starts to attract a negative rate of return, albeit a very small one. Secondly there is a progressive, though again small, decline in the marginal return to experience over time, particularly between 1988 and 1992. So for example a man in with 11 years of education and 10 years of experience at the median of the earnings distribution saw the marginal return to the 11th year of experience fall from 5.3 percent to 4.2 percent between 1988 and 1992. At the lower quintiles the fall appears to have persisted beyond 1992. This may be indicative of rapid change in the economy, as new skills become important and experience less so. Thirdly a marginal gain in experience is more highly rewarded at the top of the earnings distribution compared to the bottom. So for example a man with 11 years of

[4] 1998 does not appear to be an "rogue" observation in this respect. We find identically signed and sized coefficients using data from the 1997 PNAD.

education and 10 years of experience at the 10th quintile enjoyed a marginal return of 4.2 percent to an additional year of experience in 1988. At the 90th quintile the return would have been 6.5 percent. There is a similar difference across the distribution, although at lower absolute levels, in 1992 and 1998.

In Table 5 we report the different quintiles of the earnings distribution for each year, along with various inter-quintile differences. Actual values from each empirical distribution are reported in columns (1), (3) and (6). Between 1988 and 1992 the distribution shifts leftwards – at all points reported in the distribution, except the 25th percentile, workers experienced falls in real earnings. Between 1992 and 1998 the reverse is true. Columns (2), (4) and (7) report conditional quintiles computed from the regression model estimates, setting years of education, experience and the other controls to their average values. In effect these columns show a hypothetical earnings distribution under conditions in which all individuals have identical human capital and other characteristics. The difference between the actual and corresponding conditional distribution shows the extent to which inequality arises due to differences in endowed characteristics. A comparison of the 90-50 gaps with the 50-10 gaps shows that differences in endowed characteristics are much more important in the top half of the earnings distribution. Columns (5), (8) and (9) report points on counterfactual distributions that show how earnings would have looked in 1992 and 1998 if average levels of human capital and other characteristics had remained unchanged from the early year(s). The purpose of this is to decompose shifts in the predicted distribution into a component caused by changes in endowed characteristics from that caused by changes in the rates of return to education, experience and the other characteristics. If all men had 1988 average endowed characteristics in 1992 then the 90-10 gap would have been 1.87 rather than 1.82, with the difference more pronounced in the top half of the distribution (90-50 gap) than in the bottom half (50-10 gap). If all men had 1988 average endowed characteristics in 1998 then the 90-10 gap would have been 1.92 rather than 1.71. Here the difference is apparent in both the top and the bottom of the distribution, much is still greater in the 50-10 gap. Consequently we see that improved human capital has contributed to the narrowing in earnings inequality over the ten-year period.

Table 6 illustrates this decomposition exercise further by showing the changes in the actual (empirical) distributions and in the conditional distributions between 1988 and 1992, 1992 and 1998 and 1988 and 1998. Between 1988 and 1992 the real negative growth in earnings is sharpest at the top of the distribution (column 1), and this is what causes inequality to fall between these years. Column (2) shows that the same is true in the movement in the conditional distribution. The change in average levels of endowed characteristics hits those at the top of the distribution hardest. On the other hand if we hold mean characteristics fixed at their 1988 levels, as in column (3), then we find that improved rates of return to human capital and attributes benefit workers across the distribution. However, this benefit is larger at the bottom than at the top. Between 1992 and 1998 all points in the distribution experience real earnings growth of between 17 and 25 per cent. However the changes in the conditional distribution, reported in column (5), are largest at the bottom, and fall steadily as we move up. Consequently improvements in human capital and other characteristics have, since 1992, had most benefit for the lowest paid workers. On the other hand column (6) reveals that higher rates of return to characteristics have most benefit on earnings for those higher up the earnings distribution. Over the full ten-year period those at the bottom of the distribution have enjoyed fastest real earnings growth (column 7). The reason for this in clear in column (8) – they have benefited most from the general improvement in human capital and other remunerated characteristics in the economy. They have also seen some improvement in rates of return, particularly those around the 25th percentile, and these improvements have not been enjoyed by those at the top of the earnings distribution.

5. Conclusions

This paper has conducted an empirical investigation of the impact of education and experience across the earnings distribution for Brazilian men over the period of recent macroeconomic and trade reform. Rates of return to additional years of schooling are very high in Brazil and at the average vary between 7 and 26 per cent per year depending on levels of experience and prior education. However, rates of return to additional education are typically 4 to 7 percentage points higher at the 90th percentile of the earnings distribution compared to the 10th percentile. We find strong evidence of growing inequality in *returns* to additional years of education through the period under investigation. Since the 1980s skills have become more highly rewarded and seniority (experience) less so. Overall our results point to improved forces of competition in the labor market particular since 1992. This is particularly so because there appears to have been a shift in the role of educational qualifications from rationing or screening workers into better paid jobs towards education being rewarded because of their inherent association with higher productivity. This appears to be particularly the case in the top and bottom, as opposed to the center, of the distribution.

If the story ended there then we would expect to find strong evidence for growing earnings inequality. However this has not been a consequence of economic reform in Brazil. The reason is because significant improvements in levels of human capital have taken place, and these have contributed to a narrowing of earnings inequality. Between 1988 and 1992 during the period of high inflation and abortive stabilization attempts real earnings fell for almost all. These falls were most severe further up the earnings distribution. Improvements in *levels* of human capital and other remunerated characteristics were of most benefit to the less well paid, particularly since 1992. These improvements were significant enough to offset the adverse distributional impact of increased rates of return to education at the top of the distribution. Trade liberalization appears to have stimulated the acquisition of human capital for the less well paid. Higher rates of return, combined with an increased recognition that educational qualifications are of inherent value rather than of use purely as a signaling device, may well have stimulated increased human capital investment, alongside government and private willingness to pay.

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Table 1
Descriptive Statistics

		1988 N=65002			1992 N=67880			1998 N=74003	
		Mean	S.D.	Median	Mean	S.D.	Median	Mean	S.D.	Median
Log (hourly earnings)		0.447	1.090	0.351	0.375	1.015	0.294	0.596	1.008	0.498
Education (years)		5.440	4.368	4.000	5.651	4.310	5.000	6.332	4.357	5.000
Experience (years)		23.839	13.654	21.000	22.938	13.292	21.000	22.845	13.206	21.000
Education*Experience		99.411	93.775	78.000	101.661	93.570	81.000	117.259	102.804	96.000
Region:	North	0.082	0.274	0	0.065	0.246	0	0.071	0.257	0
	Centre East	0.129	0.335	0	0.114	0.317	0	0.118	0.322	0
	South	0.161	0.368	0	0.186	0.389	0	0.184	0.387	0
	North East	0.286	0.452	0	0.270	0.444	0	0.282	0.450	0
Metropolitan		0.407	0.491	0	0.397	0.489	0	0.397	0.489	0
Urban		0.777	0.416	1	0.814	0.389	1	0.820	0.384	1
Race:	Black	0.055	0.228	0	0.058	0.235	0	0.062	0.242	0
	Mixed	0.417	0.493	0	0.406	0.491	0	0.410	0.492	0
Log (hourly earnings)$_{q90}$ – Log (hourly earnings)$_{q10}$			2.7081			2.5107			2.4849	
Log (hourly earnings)$_{q75}$ – Log (hourly earnings)$_{q25}$			1.3732			1.2432			1.2585	

Notes: Earnings are in constant 1998 consumer prices. The base region is the South East, and the base racial group is white.

Table 2
Regression Estimates

	1988						1992					
	OLS	Q10	Q25	Q50	Q75	Q90	*OLS*	Q10	Q25	Q50	Q75	Q90
Education	0.1185*	0.0891*	0.0686*	0.0959*	0.1301*	0.1644*	0.0960*	0.0840*	0.0703*	0.0767*	0.1059*	0.1127*
	(0.0043)	(0.0065)	(0.0058)	(0.0048)	(0.0057)	(0.0081)	(0.0041)	(0.0077)	(0.0066)	(0.0046)	(0.0050)	(0.0079)
Education^2	0.0040*	0.0038*	0.0055*	0.0052*	0.0041*	0.0026*	0.0039*	0.0028*	0.0043*	0.0049*	0.0042*	0.0043*
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0004)
Experience	0.0778*	0.0669*	0.0622*	0.0725*	0.0843*	0.0948*	0.0632*	0.0556*	0.0539*	0.0582*	0.0684*	0.0744*
	(0.0016)	(0.0026)	(0.0019)	(0.0018)	(0.0022)	(0.0029)	(0.0015)	(0.0028)	(0.0022)	(0.0018)	(0.0016)	(0.0026)
Experience^2	-0.0010*	-0.0009*	-0.0009*	-0.0010*	-0.0011*	-0.0012*	-0.0008*	-0.0008*	-0.0008*	-0.0008*	-0.0009*	-0.0009*
	(0.00002)	(0.00004)	(0.00003)	(0.00003)	(0.00003)	(0.00004)	(0.00002)	(0.00004)	(0.00003)	(0.00002)	(0.00002)	(0.00004)
Education*	-0.0004*	-0.0006*	0.0001	0.00001	-0.0003*	-0.0006*	-0.0004*	-0.0006*	-0.0002	-0.0001	-0.0004*	-0.0004*
experience	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
N	65002						67880					
R^2/Pseudo R^2	0.484	0.229	0.248	0.291	0.327	0.339	0.448	0.227	0.230	0.270	0.296	0.306
Wald χ^2 (19)	846.09						1440.61					

Table 2 (continued)

	1998					
	OLS	Q10	Q25	Q50	Q75	Q90
Education	0.0410* (0.0038)	0.0197* (0.0060)	0.0175* (0.0054)	0.0254* (0.0047)	0.0552* (0.0045)	0.0749* (0.0053)
Education^2	0.0067* (0.0002)	0.0061* (0.0003)	0.0067* (0.0002)	0.0074* (0.0002)	0.0069* (0.0002)	0.0063* (0.0003)
Experience	0.0544* (0.0014)	0.0429* (0.0022)	0.0452* (0.0017)	0.0515* (0.0016)	0.0613* (0.0014)	0.0672* (0.0024)
Experience^2	-0.0007* (0.00002)	-0.0007* (0.00003)	-0.0007* (0.00002)	-0.0007* (0.00002)	-0.0008* (0.00002)	-0.0008* (0.00004)
Education* experience	0.00024* (0.00007)	0.00025+ (0.00013)	0.00053* (0.00010)	0.00062* (0.00010)	0.00027* (0.00008)	0.00007 (0.00013)
N	74003					
R^2/Pseudo R^2	0.490	0.217	0.264	0.303	0.335	0.341
Wald χ^2 (19)		155.84				

Notes: All equations also include four regional dummy variables, dummy variables for metropolitan and urban status, dummy variables for racial group (black, mixed raced) and interactions of the race dummies with schooling and with experience. Full results available on request. Simultaneous quintile regression standard errors obtained by bootstrapping (100 replications). Wald is a test for combined equality of the reported schooling and experience coefficients across all quintiles. * denotes significance at 5% or less; + denotes significance at 10%.

Source: authors' calculations from PNAD 1988, 1992 and 1998

Table 3
Estimated Rates of Return to an Additional Year of Schooling

Years:		1988						1992					
Education	Experience	*OLS*	Q10	Q25	Q50	Q75	Q90	*OLS*	Q10	Q25	Q50	Q75	Q90
2	10	*0.130*	0.099	0.092	0.117	0.146	0.169	*0.107*	0.090	0.086	0.095	0.119	0.126
2	20	*0.126*	0.093	0.093	0.117	0.144	0.164	*0.103*	0.084	0.084	0.095	0.116	0.122
2	30	*0.122*	0.088	0.095	0.117	0.141	0.158	*0.099*	0.079	0.082	0.094	0.112	0.118
2	40	*0.118*	0.082	0.096	0.118	0.138	0.152	*0.095*	0.073	0.081	0.093	0.109	0.114
6	10	*0.162*	0.129	0.136	0.159	0.179	0.190	*0.139*	0.113	0.120	0.134	0.153	0.160
6	20	*0.158*	0.123	0.137	0.159	0.177	0.185	*0.135*	0.107	0.118	0.134	0.149	0.156
6	30	*0.154*	0.118	0.139	0.159	0.174	0.179	*0.130*	0.102	0.117	0.133	0.146	0.152
6	40	*0.150*	0.112	0.140	0.159	0.172	0.173	*0.126*	0.096	0.115	0.132	0.142	0.149
11	10	*0.202*	0.167	0.191	0.211	0.221	0.217	*0.178*	0.141	0.163	0.183	0.195	0.203
11	20	*0.198*	0.161	0.192	0.211	0.218	0.211	*0.174*	0.136	0.161	0.182	0.191	0.199
11	30	*0.194*	0.156	0.193	0.212	0.216	0.205	*0.170*	0.130	0.160	0.181	0.188	0.195
11	40	*0.190*	0.150	0.195	0.212	0.213	0.200	*0.165*	0.125	0.158	0.181	0.184	0.192
16	10	*0.243*	0.205	0.245	0.264	0.262	0.243	*0.217*	0.170	0.206	0.232	0.237	0.246
16	20	*0.238*	0.199	0.247	0.264	0.260	0.237	*0.213*	0.164	0.205	0.231	0.234	0.242
16	30	*0.234*	0.194	0.248	0.264	0.257	0.232	*0.209*	0.159	0.203	0.230	0.230	0.238
16	40	*0.230*	0.188	0.249	0.264	0.254	0.226	*0.205*	0.153	0.201	0.229	0.227	0.234

Table 3 (continued)

Years: Education	Experience	1998 *OLS*	Q10	Q25	Q50	Q75	Q90
2	10	*0.070*	0.047	0.050	0.061	0.085	0.101
2	20	*0.072*	0.049	0.055	0.067	0.088	0.101
2	30	*0.075*	0.051	0.060	0.074	0.091	0.102
2	40	*0.077*	0.054	0.066	0.080	0.093	0.103
6	10	*0.123*	0.095	0.103	0.120	0.140	0.151
6	20	*0.126*	0.098	0.109	0.127	0.143	0.152
6	30	*0.128*	0.100	0.114	0.133	0.146	0.153
6	40	*0.131*	0.103	0.119	0.139	0.148	0.153
11	10	*0.190*	0.157	0.171	0.194	0.209	0.214
11	20	*0.193*	0.159	0.176	0.201	0.212	0.215
11	30	*0.195*	0.162	0.181	0.207	0.215	0.216
11	40	*0.197*	0.164	0.187	0.213	0.217	0.216
16	10	*0.257*	0.218	0.238	0.268	0.278	0.277
16	20	*0.259*	0.220	0.243	0.275	0.281	0.278
16	30	*0.262*	0.223	0.248	0.281	0.284	0.279
16	40	*0.264*	0.225	0.254	0.287	0.286	0.279

Source: computed from results reported in Table 2.

Table 4
Estimated Rates of Return to an Additional Year of Experience

Years:		1988						1992					
Education	Experience	*OLS*	Q10	Q25	Q50	Q75	Q90	*OLS*	Q10	Q25	Q50	Q75	Q90
2	10	*0.057*	0.047	0.045	0.053	0.062	0.070	*0.046*	0.039	0.038	0.042	0.050	0.056
2	20	*0.036*	0.028	0.028	0.034	0.041	0.047	*0.029*	0.023	0.023	0.027	0.033	0.039
2	30	*0.016*	0.009	0.010	0.014	0.019	0.024	*0.013*	0.007	0.008	0.011	0.015	0.021
2	40	*-0.004*	-0.010	-0.007	-0.005	-0.003	0.001	*-0.003*	-0.009	-0.007	-0.005	-0.002	0.003
6	10	*0.055*	0.045	0.046	0.053	0.061	0.068	*0.044*	0.036	0.038	0.042	0.049	0.054
6	20	*0.035*	0.026	0.028	0.034	0.040	0.045	*0.028*	0.021	0.022	0.026	0.032	0.037
6	30	*0.014*	0.007	0.011	0.014	0.018	0.022	*0.011*	0.005	0.007	0.011	0.014	0.019
6	40	*-0.006*	-0.012	-0.007	-0.005	-0.004	-0.001	*-0.005*	-0.011	-0.008	-0.005	-0.003	0.002
11	10	*0.053*	0.042	0.046	0.053	0.060	0.065	*0.042*	0.034	0.037	0.042	0.047	0.053
11	20	*0.033*	0.023	0.029	0.034	0.038	0.042	*0.026*	0.018	0.022	0.026	0.030	0.035
11	30	*0.012*	0.004	0.011	0.015	0.017	0.019	*0.009*	0.002	0.006	0.010	0.012	0.017
11	40	*-0.008*	-0.015	-0.006	-0.005	-0.005	-0.004	*-0.007*	-0.014	-0.009	-0.005	-0.005	0.000
16	10	*0.051*	0.039	0.047	0.053	0.059	0.062	*0.040*	0.031	0.036	0.041	0.045	0.051
16	20	*0.031*	0.020	0.030	0.034	0.037	0.039	*0.024*	0.015	0.021	0.026	0.028	0.033
16	30	*0.010*	0.001	0.012	0.015	0.015	0.016	*0.007*	-0.001	0.006	0.010	0.011	0.015
16	40	*-0.010*	-0.018	-0.005	-0.005	-0.006	-0.007	*-0.009*	-0.016	-0.010	-0.006	-0.007	-0.002

Table 4 (continued)

Years:		1998					
Education	Experience	*OLS*	Q10	Q25	Q50	Q75	Q90
2	10	*0.040*	0.030	0.033	0.038	0.046	0.052
2	20	*0.026*	0.017	0.019	0.024	0.031	0.037
2	30	*0.011*	0.003	0.005	0.010	0.015	0.021
2	40	*-0.003*	-0.010	-0.008	-0.005	0.000	0.006
6	10	*0.041*	0.031	0.035	0.041	0.047	0.052
6	20	*0.027*	0.018	0.021	0.026	0.032	0.037
6	30	*0.012*	0.004	0.008	0.012	0.016	0.022
6	40	*-0.002*	-0.009	-0.006	-0.002	0.001	0.006
11	10	*0.043*	0.032	0.037	0.044	0.049	0.053
11	20	*0.028*	0.019	0.024	0.030	0.033	0.037
11	30	*0.014*	0.006	0.010	0.015	0.018	0.022
11	40	*-0.001*	-0.008	-0.003	0.001	0.002	0.007
16	10	*0.044*	0.034	0.040	0.047	0.050	0.053
16	20	*0.029*	0.020	0.027	0.033	0.035	0.038
16	30	*0.015*	0.007	0.013	0.018	0.019	0.022
16	40	*0.000*	-0.006	-0.001	0.004	0.003	0.007

Source: computed from results reported in Table 2.

Table 5
Actual and Conditional Log Hourly Earnings Distributions

	1988		1992			1998			
	(1) *Actual*	(2) Conditional	(3) *Actual*	(4) Conditional	(5) Conditional at 1988 means	(6) *Actual*	(7) Conditional	(8) Conditional at 1988 means	(9) Conditional at 1992 means
Q10	*-0.788*	-0.478	*-0.805*	-0.526	-0.444	*-0.550*	-0.246	-0.461	-0.369
Q25	*-0.293*	-0.043	*-0.256*	-0.084	-0.013	*-0.086*	0.148	-0.010	0.073
Q50	*0.351*	0.431	*0.294*	0.368	0.458	*0.498*	0.577	0.453	0.560
Q75	*1.080*	0.924	*0.987*	0.833	0.949	*1.173*	1.019	0.927	1.062
Q90	*1.920*	1.408	*1.706*	1.293	1.430	*1.935*	1.464	1.393	1.550
Q90-Q10	*2.708*	1.886	*2.511*	1.819	1.874	*2.485*	1.711	1.854	1.919
Q75-Q25	*1.373*	0.963	*1.243*	0.917	0.962	*1.258*	0.871	0.937	0.988
Q90-Q50	*1.569*	0.977	*1.412*	0.925	0.971	*1.437*	0.888	0.940	0.990
Q50-Q10	*1.139*	0.909	*1.099*	0.894	0.903	*1.048*	0.823	0.914	0.929

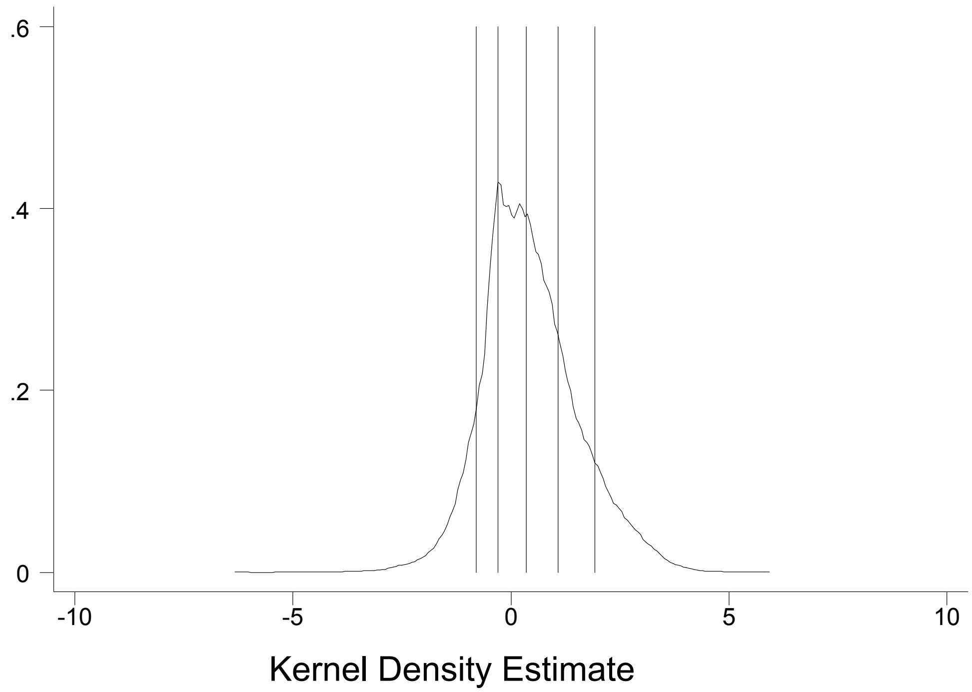
Source: computed from results reported in Table 2

Table 6
Earnings Growth Across the Distribution

	1988-1992			1992-1998			1988-1998		
	(1) *Actual*	(2) Conditional	(3) Conditional at 1988 means	(4) *Actual*	(5) Conditional	(6) Conditional at 1992 means	(7) *Actual*	(8) Conditional	(9) Conditional at 1988 means
Q10	*-0.016*	-0.048	0.034	*0.254*	0.279	0.157	*0.238*	0.232	0.017
Q25	*0.037*	-0.040	0.030	*0.170*	0.231	0.157	*0.207*	0.191	0.033
Q50	*-0.057*	-0.063	0.027	*0.203*	0.209	0.192	*0.147*	0.146	0.022
Q75	*-0.093*	-0.091	0.025	*0.186*	0.186	0.229	*0.093*	0.095	0.003
Q90	*-0.214*	-0.115	0.021	*0.229*	0.171	0.257	*0.015*	0.056	-0.015

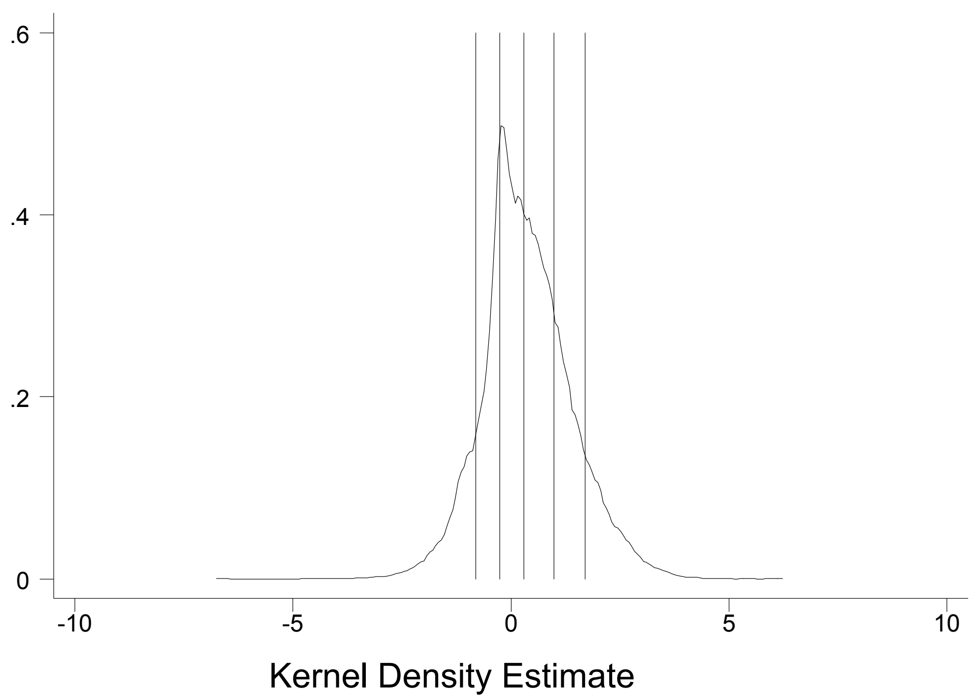
Source: computed from results reported in Table 2.

Figure 1: Univariate Kernel Density Estimates for Log Hourly Earnings - 1988



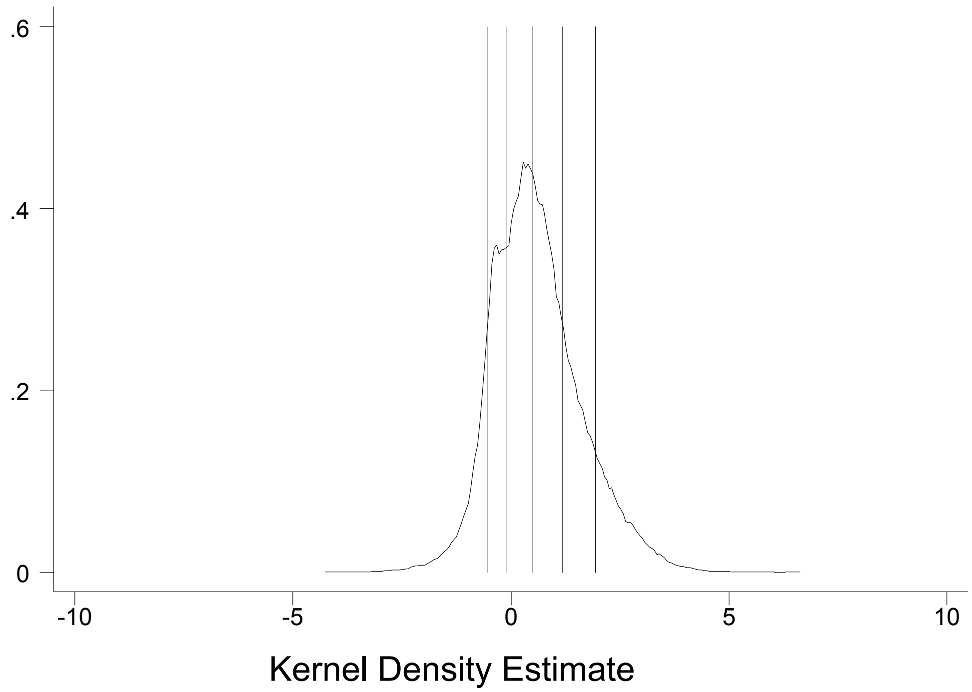
Note: vertical lines indicate positions of 10th, 25th, 50th, 75th and 90th percentiles.

Figure 2: Univariate Kernel Density Estimates for Log Hourly Earnings - 1992



Note: vertical lines indicate positions of 10th, 25th, 50th, 75th and 90th percentiles.

Figure 3: Univariate Kernel Density Estimates for Log Hourly Earnings – 1998



Note: vertical lines indicate positions of 10th, 25th, 50th, 75th and 90th percentiles.